Reinforcement Learning 2

Complications & approximations

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Introduction

Plan for this lecture

Talk about all the stuff that makes it messy:

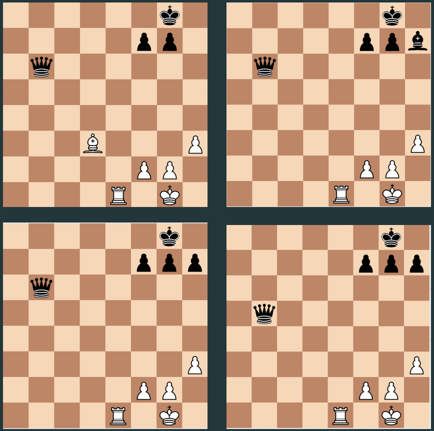
  

- Infinite spaces & approximations.
- Correlations & replay.
- Exploration & on/off-policy learning.
- Unobservables & POMDPs, different assumptions and other approaches.

Function approximation

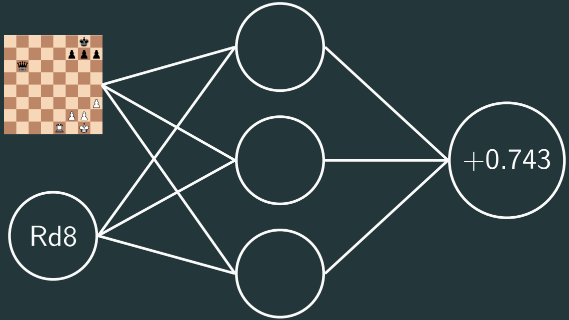
Similarities & dissimilarities

- More state, action pairs in chess than atoms in observable universe.
- However…



Approximating the Q-table

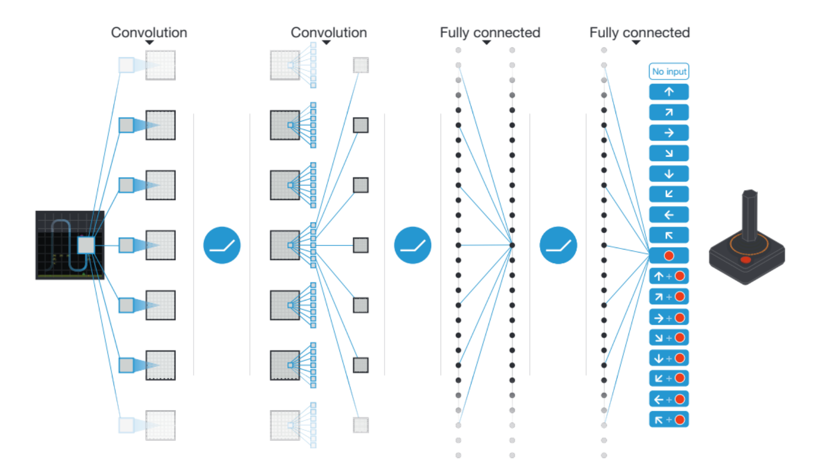
- Previously, the Q-table was a lookup function. Let's replace this with some other function that maps states and actions to Q-values.



- Loss:

$$L = \left(r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a'; \theta_i^-) - Q(s_t, a_t; \theta_i) \right)^2$$

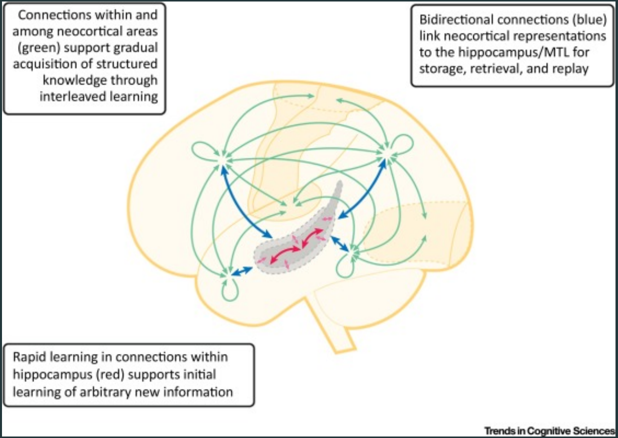
Playing atari games



Replay

Fix one problem and ...

- Generalization comes at the expense of cross talk and catastrophic forgetting. Will a self-driving car learning to parallel park forget how to drive on the freeway?
- CLS is a theory of how humans and animals avoid this:



Replay buffers

The Atari game-playing paper addressed this with **experience replay**:

- Whenever we experience a new $(s_t, a_t, r_{t+1}, s_{t+1})$ tuple, stick it in a buffer.
- instead of

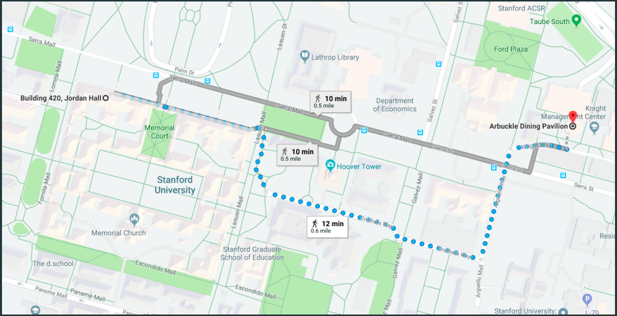
$$\Delta Q^{\pi}(s_t, a_t) = \alpha \underbrace{\left(\left[r_{t+1} + \max_{a'} \gamma Q^{\pi}(s_{t+1}, a')\right] - Q(s_t, a_t)\right)}_{\text{prediction error!}}$$

we sample a random experience from our buffer and update with that: $k \sim \mathit{Unif}(\text{replay buffer indices})$

$$\Delta Q^{\pi}(s_k, a_k) = \alpha \underbrace{\left(\left[r_{k+1} + \max_{a'} \gamma Q^{\pi}(s_{k+1}, a')\right] - Q(s_k, a_k)\right)}_{\text{prediction error!}}$$

Exploration and exploitation and on/off policy

The need to explore



- How do I trade off between **exploiting** the best path to lunch I've found so far and **exploring** my other options?
- In other words, how do we incorporate exploration into our policy?
- This is important – remember convergence guarantees required *every* state, action pair to be visited "frequently."

The exploration-exploitation trade-off

There is a *fundamental* trade-off between exploring and exploiting:

- Exploring wastes time trying things I'm pretty sure aren't good.
- Exploiting risks missing a great opportunity.
- We have to find some balance between these that results in good payoffs but still makes sure we don't miss too much.

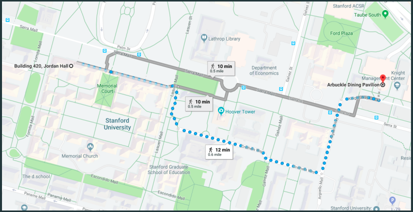
ϵ-greedy

- One simple technique is just to choose actions randomly some small fraction ϵ of the time.
- The rest of the time, take the maximum Q action.
- We call this ϵ-greedy.
- We can also do clever things like *anneal* ϵ over training.
    - Act mostly randomly and explore a lot early in training.
    - Act mostly greedily and exploit a lot late in training/in testing.

Exploit during testing or keep exploring?

The point about testing vs. training is a little tricky...

- Do chess players stop learning when they're playing for the world championship?
- A self-driving car can't just be trained and set free – destinations, roads, and laws are all evolving.
- What if my direct path to lunch was blocked by a building that was torn down?



Non-optimality of Q-learning under exploration

- But Q-learning fundamentally assumes that we will be behaving completely greedily during training! Why?
- It's built into our computation of the Q-update:

$$\Delta Q^{\pi}(s_t, a_t) = \alpha\left(\left[r_{t+1} + \max_{a'} \gamma Q^{\pi}(s_{t+1}, a')\right] - Q(s_t, a_t)\right)$$

- If we want to behave optimally with a policy π that explores, we have to incorporate this policy into the learning rule:

$$\Delta Q^{\pi}(s_t, a_t) \stackrel{?}{=} \alpha\left(\left[r_{t+1} + \sum_{a'} p(a' | s_t, a_t, s_{t+1}, \pi)\, \gamma Q^{\pi}(s_{t+1}, a')\right] - Q(s_t, a_t)\right)$$

SARSA

- One algorithm for doing this is SARSA. It works almost exactly like Q learning, except we store $(s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1})$
- and change our update from

$$\Delta Q^\pi(s_t, a_t) = \alpha\left(\left[r_{t+1} + \max_{a'} \gamma Q^\pi(s_{t+1}, a')\right] - Q(s_t, a_t)\right)$$

to

$$\Delta Q^\pi(s_t, a_t) = \alpha([r_{t+1} + \gamma Q^\pi(s_{t+1}, a_{t+1})] - Q(s_t, a_t))$$

- Since our actions in the state are distributed according to π, in expectation our Q-value updates will be as well.

On/off-policy

This highlights an important, but somewhat orthogonal distinction:

- Do we want to learn **on-policy**, that is, using the same policy we will be using during evaluation (like SARSA)?
- Or do we want to learn **off-policy**, that is, using a different policy during training than during evaluation (like Q-learning)?

There are tradeoffs!

- **On-policy:** Can be faster, can be more stable.
- **Off-policy:** Can learn from anything, even totally random play – incorporating more early exploration or replay easier.

Wrapping up

Summary

- We have an **agent** that takes **actions** in **states**.
- These actions are chosen according to a **policy**, sometimes derived from some sort of **value function**.
- We evaluated on **expected discounted rewards.**
- The **discount** reflects how future-oriented we are.
- $Q^{\pi}(s, a)$ is the expected return of a in s under π.
- We can learn Q values by **TD learning** (surprise).
- Can approximate Q using deep learning (for generalization).
- There's a trade-off between **exploring** and **exploiting**!
- ... and there's way more to RL than will fit on one slide or one course.

Other approaches

Many other approaches:

- Policy gradient methods.
- Actor-critic methods.
- Many, many variations.

And under different assumptions:

- What if we only observe part of the state? (POMDPs.)
- What if we actually build models of the world and plan over these? (Model-based RL, as opposed to Model-free.)
- ... Or something in between? (Successor-representation, imagination.)
- And much more.